Single and Multi-Objective Genetic Algorithms for the Container Loading Problem

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ABSTRACT

Container Loading Problems (CLPs) deal with determination of the optimal pattern for packing boxes into a given container usually with respect to the maximal utilization of the total container volume. On the other hand, it is also important to maximize the utilization of the maximal container weight for which is paid when buying a shipment service. In this paper we analyze two genetic algorithms specially adopted to solve CLP. One of them is based on the Genetic Algorithm (GA) and is suitable to solve single-objective CLPs, while another one is based on the Non-dominated Sorting Genetic Algorithm (NSGA-II), suitable for solution of CLP by simultaneously considering both of the above mentioned objectives. The algorithms have been experimentally investigated by solving various CLP instances of different complexity. The obtained results showed that simultaneous consideration of both objectives using the proposed multi-objective optimization algorithm gives better results in utilization of container volume when solving complex CLP instances.

CCS CONCEPTS

•**Computing methodologies** → **Artificial intelligence;** •**Applied computing** → *Operations research;* •**Mathematics of computing** → Discrete mathematics; •**Theory of computation** → Design and analysis of algorithms;

KEYWORDS

Container loading, multi-objective optimization, evolutionary algorithms, genetic algorithms, multi-objectivization.

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1 INTRODUCTION

The *Container Loading Problem* (CLP) belongs to the family of cutting and packing problems [2]. Although the problem itself intrinsically deals with several objectives and constraints, the most common approaches found in the literature deal with single-objective formulations of the problem. This way, the optimization process is focused on a single objective (usually, the maximization of the container volume utilization) while the other objectives are relegated to a lower level of priority. However, when solving a real CLP there are many practical issues that may be taken into account [1]. For example, rented trucks to transport the shipment are paid according to the total weight they can transport regardless of the total volume. Thus, the decision maker prefers to load and ship a shipment with high total weight rather than a shipment with low total weight. For that reason, in this work we take the total weight as a second and desirable objective. Then, the problem can be stated as a multi-objective optimization problem, trying to optimize the pieces layout inside the container so that the volume is maximized at the same time that the weight, without exceeding the weight limit. It might appear that the total volume maximization implies a maximization of weight. However, usually the size of the pieces or boxes to pack in the container is not proportional to their weight. That is, a box can be large and the content thereof may be lighter than a the content of a smaller box. Furthermore, it's also remarkable that in this work the problem will be solved using the following assumptions: each box is placed in the container floor or on top of another box and the stability of the distribution of the boxes is not considered.

2 SINGLE AND MULTI-OBJECTIVE APPROACHES

We propose the solution of the CLP from two different points of view: on the one hand we apply a single-objective genetic algorithm focused on the maximization of the overall volume and on the other hand we apply a well-known Pareto-based method for multi-objective optimization denoted as *Fast Non-Dominated Sorting Genetic Algorithm* (NSGA-II) [4]. For the multi-objective approach we consider the maximization of the container's weight utilization as the second (or extra) objective. This way, we will be able to compare a method that introduces user preferences a priori – completely focusing on the optimization of a single objective to take advantage of the simplicity and power of single-objective methods – with a method that do not decide a priori information about the relevance of the two given objectives; it only takes into account the

Table 1: Results obtained by single-objective GA and multi-objective NSGA-II

$[D_l - D_h]$	Box types	Volume GA	Volume NSGA-II	Weight GA	Weight NSGA-II
[5 − 10]	5	**98.90**	98.76	**95.20**	94.03
[15 − 20]	5	93.21	**97.15**	**86.25**	77.96
[25 − 30]	5	89.56	**96.70**	**90.38**	77.65
[5 − 10]	8	**97.11**	96.64	**88.76**	87.66
[15 − 20]	8	93.18	**97.83**	78.80	**79.25**
[25 − 30]	8	92.17	**95.69**	**94.57**	81.43
[5 − 10]	10	**96.74**	96.44	88.18	**94.75**
[15 − 20]	10	93.81	**94.54**	79.39	**93.05**
[25 − 30]	10	91.43	**93.95**	82.51	**86.61**

preferences of the user a posteriori, when a set of non-dominated solutions has been already obtained.

For the application of the GAs we have applied a problem-specific codification [3] combined with a placement heuristic based on the generation on levels and the completion of smaller empty spaces first [6]. Such a placement heuristic analyzes the pieces encoded in a solution and gives a concrete distribution of the pieces inside the container, so that is then possible to calculate the total volume utilization and total weight of items loaded into the container, thus obtaining the values for the problem objectives: the volume and the weight. Every candidate solution is encoded as a sequence formed by piece type, number of pieces of that type and rotation for those pieces. This will determine the order in which the pieces will be considered – by the placement heuristic – to be inserted into the container as well as their given orientations.

We have defined a method to generate the candidate solutions in the initial population and a set of evolutionary operators. For the single-objective GA a uniform crossover operator is applied. Such a crossover procedure can produce an individual violating problem constraints by enumerating too much or too less boxes of a certain type. Therefore, a mutation operator is applied in order to fit the offspring individual into the problem constraints. For the multi-objective GA a one point crossover operator, which ensures the problem constraints has been used. In this case, for the mutation we have introduced three different types of movements on the chromosome: add one gene, remove a gene, and change a gene [6].

3 EXPERIMENTAL EVALUATION

Problem instances dealing with the multi-objective formulation of the CLP here proposed are almost inexistent [5]. For this reason, we have generated a set of instances with different properties and complexity [7]. The box set of the different instances vary from small to large sized boxes. To determine the box sizes, the generator of instances requires two input parameters (D_l and D_h), which determine the lowest and highest dimensions that a box can have with respect to the dimensions of the container. For the execution of the GAs, the population size has been chosen to be 20 individuals and 100 generations have been performed thus performing 2000 function evaluations in total. Due to stochastic nature of the algorithms, 30 independent runs have been performed for each instance and average result has been recorded.

In order to compare both approaches, from the set of solutions given by a single run of the multi-objective approach, the solution point with the highest volume was selected and average values of such volumes were considered. The weight values for such solutions "in volume" has been be also analyzed (see Table 1). Single-objective optimization GA slightly outperforms multi-objective NSGA-II on simple instances, where $[D_l - D_h] = [5 - 10]$. Such instances manage smaller box sizes, so the differences between introducing one or another box is not so significant as when dealing with larger box sizes: small sized boxes are more easily located inside the container. However, NSGA-II notably outperforms GA on more complex instances. Moreover, the more complex instance, the larger difference between average volumes obtained by the algorithms under investigation. If the results for the secondary objective – in percentage of weight utilization – are analyzed, we can realize that the multi-objective approach outperforms the single-objective one when the instances deal with a higher number of box types.

4 CONCLUSIONS AND FUTURE WORK

In this work, we propose to apply a multi-objective evolutionary algorithm in order to solve the CLP. Instead of adding an extra and problem-independent objective, we have decided to consider a second objective which is inherent to the problem and which deals with another limitation within the containers: "the weight". Thus, having a multi-objective formulation we can apply a multi-objective algorithm which can be then compared to a single-objective approach. Both approaches – single and multi-objective – are based on the fundamentals of genetic algorithms. Preliminary results reveal that the application of multi-objective approaches can be promising, even when the user is interested on one single objective. In order to obtain a further analysis, other single-objective approaches for the CLP should be compared.

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